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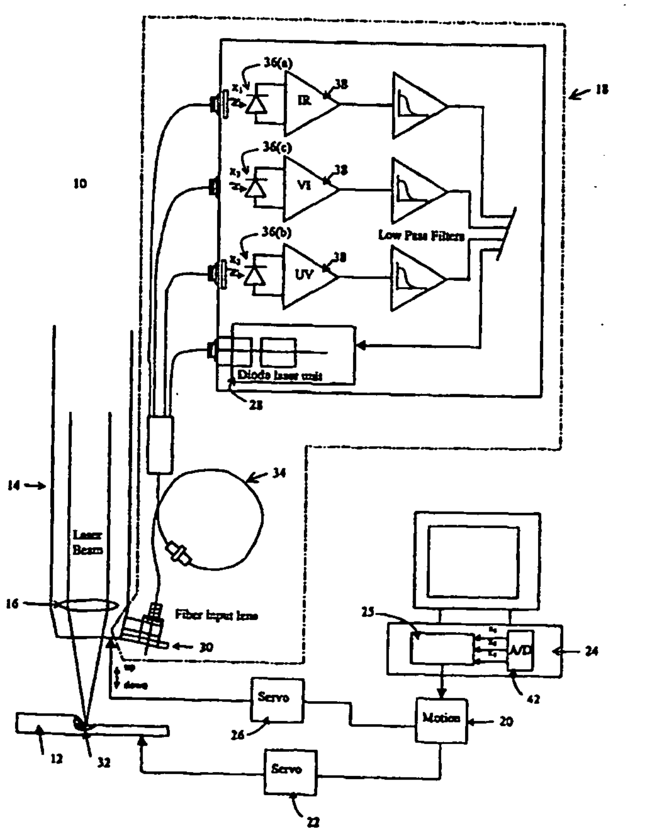
(57) Abstract

There is provided a control system for laser processing of a material, the system comprises a sensor for receiving electromagnetic emissions from a weld zone; a fuzzy logic subsystem for processing said sensor outputs directly to produce a weld quality output signal; and a neural network subsystem using input data frequency from said sensor outputs and said weld quality signal to develop a weld parameter control signal, whereby the neural network is capable of detecting extradinary events in the incoming data stream while the fuzzy logic controller is capable of detecting trends in the incoming data stream.



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SELF-ADAPTING NEURAL-FUZZY NETWORK FOR REAL-TIME PROCESS CONTROL

The present invention relates to intelligent systems and in particular to intelligent controllers using neural-network based fuzzy logic controllers for real-time control of laser welding.

BACKGROUND OF THE INVENTION

Uses of intelligent controllers have become more numerous and varied in keeping with the complex and stringent control requirements of modern manufacturing and electronics systems. For example intelligent controllers have been used in such applications ranging from automatic commuter train controllers to robotic mechanisms.

Laser processing of materials such as laser welding, laser annealing, laser cutting and laser cladding of metals and non-metals alike has become an invaluable tool in many industries. For example, laser welding of metal in any joint configuration involves the use of laser radiation to heat the surface to temperatures at which melting and in the case of penetration or "key-hole" welding, some material vaporization occurs. The size of the localized area on the surface joint where this process takes place can be adjusted by an external means. Usually this involves a focusing lens or mirror to adjust the focal point of the laser beam. However the quality of the weld (weld's penetration, morphology, porosity and metallurgical characteristics) can be effected by a number of factors, some of which may rapidly fluctuate during the welding process.

Forming and maintaining the laser keyhole for the purpose of welding metals is an inherently unstable process. This instability usually leads to weld defects, which in turn results in creation of scrap during industrial production of parts. There are two potential courses of action to prevent shipping of defective laser welded parts to downstream customers in the production chain: (a) monitoring the welding process, identifying the defective part and subsequently removing it from the production stream; and (b) establishing a real-time, closed loop control of the laser welding process and hence, minimizing the formation of defective parts.

The principal variables which can be used to characterize a laser process are divided into three categories; 1) laser beam characteristics such as laser power, beam mode, temporal profile etc.; 2) laser beam delivery characteristics such as process speed, focal position and

the like; and 3) physical and chemical properties of the workpiece such as reflectivity which has an impact on the laser material interaction and surface contamination.

The phrase "laser processing" as used herein refers to processes such as laser welding, cladding etc. and the phrase "process speed" as used herein means rate (distance per unit time or area per unit time) at which the process occurs. This process speed is related to the rate at which a sufficient amount of energy from the laser beam is converted to heat in the workpiece (energy per unit length). The laser processing may be achieved either by scanning the workpiece under a fixed laser beam or vice versa or by changing the laser pulse repetition rate, duty cycle and the temporal pulse profile. When the process is laser welding the process speed is the welding speed. Thus to maintain a stable welding process corresponding adjustments in laser power, welding speed or focal position are required.

There are two possible sources of information, which can be used as inputs to a controller for implementing a decision-making scheme to control the weld quality during welding. These are acoustic emissions and electromagnetic emissions from the keyhole and, in some cases, its plasma. A controller can utilize either one or both of these information sources to make various decisions.

One approach is to identify lower and upper acceptable limits for chosen system inputs. At any point during the weld, if the input exceeds either one of these limits then the part can be identified as defective. It is also possible to devise schemes where the upper and lower bounds have some flexibility to prevent excessive triggering of the system. Another common approach is to sample the chosen inputs and store the input values during the weld thereby establishing a weld signature. Upon completion of the weld, the stored weld signature is compared to pre-established "good" weld signatures. The correlation between the current signature and the good weld signatures is then used to form a decision on the quality of the weld.

There are commercially available systems in the market using the above-described schemes but the industrial effectiveness of these systems has been less than satisfactory. In many instances monitoring systems were installed on laser welders but within a relatively short production time there are generally turned off or removed with the complaint that they were either leading to too many false alarms or allowing faulty parts through.

Welding usually involves fixturing of the part. There is always some inherent

variability in the manner two parts are fixtured in relation to each other. The cumulative effects of these variations lead to a situation where even though the welding conditions change to a very large degree the resultant weld signatures are always compared to a pre-fixed, "good" weld. As a result, if the correlation coefficient is tightened then the system creates false triggers. On the other hand, loosening of the correlation coefficient leads to shipping of bad parts.

The dissatisfaction with these systems stems from the fact that the materials to be welded and the weld condition they lead to change constantly. The reality of the production environment is that as the steel coil changes, the alloy composition, coating quality, mill oil content changes. Furthermore, the upstream production processes associated with the making of the parts to be welded also change in time. Thus, monitoring schemes that utilize fixed, pre-established criteria of a good weld to make a decision are not very effective in accommodating variability associated with production environment.

One approach to prevent shipping of faulty components downstream in the production chain is the use of self-adapting neural fuzzy networks in the real-time process control of laser welding. The key phrase "self-adapting" refers to the absence of pre-established criteria of a good weld signature.

Fuzzy logic controllers for laser welding have been developed allowing real time control of the process and allowing optimization of the weld parameters. Neural-network controllers have also been proposed. The application of neural-networks to learn system behavior has been suggested to overcome some of the problems associated with fuzzy logic based designs. Using systems input and output data a neural-network can learn the system behavior and accordingly generate fuzzy logic rules.

By way of background a neural-network process input electrical signals in a way which enables patterns represented by the signals to be recognized. They are set up by causing the values of components in the circuit to be modified repeatedly until the required output is produced in response to the input of the signaled pattern to be recognized. The process is considered to model the process of memory and recognition in the human brain, hence their description as "neural" networks. These devices generally can be made up of permanently wired circuits or can be created within a computer by appropriate software.

Of all types of controllers, neural-networks are the most effective way to implement

an intelligent controller. Back propagation neural-networks is one of the most widely used methods for training multi-layer neural-networks. On the other hand feed forward networks may be more effective in some situations. There is considerable overlap between the fields of neural-networks and statistics. Statistics are concerned with data analysis. In neural-network terminology statistical inference means learning to generalize from noisy data. For example, identify an extraordinary event from an ordinary event. In the area of electronic controllers the term "habituation" refers to the learning process of neural-networks. A neural-network "learns" by reinforcing or diminishing the interconnections between nodes. This process is based on perfecting the output. It is the process of adjusting these interconnections to optimize the output that is called habituation.

SUMMARY OF THE INVENTION

It is an object of the present invention to provide a laser processing control system which controls in real-time laser processing variables based on feedback from sensor monitoring the laser material interaction zone.

It is a further object of the invention to provide a neural network architecture that is capable of detecting extraordinary events in an input data stream.

In accordance with the invention, there is provided a control system for laser processing of a material, the system comprises

(a) a sensor for receiving electromagnetic emissions from a weld zone;
(b) a fuzzy logic subsystem for processing said sensor outputs to produce a weld quality output signal; and
(c) a neural network subsystem using said sensor outputs and said weld quality signal to develop a weld parameter control signal.

BRIEF DESCRIPTION OF THE DRAWINGS

Embodiments of the present invention will now be described by way of example only with reference to the accompanying drawings in which:

Figure 1 is a diagrammatic representation of a laser welding apparatus constructed in accordance with the present invention showing the system components and data pathways using electromagnetic radiation sensors;

Figure 2 is a schematic diagram of a fuzzy-neural processing subsystem;

Figure 3 shows the input membership functions for a fuzzy logic inference engine;

Figure 4 draws the rule tables for the fuzzy logic controller;

Figure 5 shows the respective control surfaces for each of the membership functions in figure 4; and

Figure 6(a), (b) and (c) show a detailed representative of a neural network channel.

DETAILED DESCRIPTION OF A PREFERRED EMBODIMENT

Referring to figure 1, the system components and data pathways for a laser processing system for processing a workpiece 12 is shown generally by numeral 10. The system comprises a laser 14 and focusing optics 16, an electromagnetic radiation sensor subsystem 18, a motion control subsystem 20, the output of which drives amplifiers and servo motors shown at 22 and 26 used to control the motion of workpiece 12 and the beam spot size respectively. A computer system 24 receives signals from the sensor subsystem 18, and processes this data in a sensor processing subsystem 25 to produce control signals to the motion control subsystem 20. The servo 26 moves the laser 14 up or down, thereby varying the spot size at the weld zone.

The sensor subsystem 18 includes a lens 30, which is focused and aligned on the weld zone 32 by aid of a diode laser 28. The input lens 30 transmits the received electromagnetic radiation from the weld zone 32 via an optical fiber cable 34 to a series of three light sensors 36(a), 36(b) and 36(c) respectively. The sensors are photodiodes, which include filters to select respectively the infrared (IR), ultra-violet (UV) and visible (VI) light spectrum. Each of the photodiode outputs are amplified by op-amps 38, the outputs of which are passed through respective low-pass filters to produce varying amplitude signals corresponding to the intensity of the received light. Each of the amplitude signals is digitized by analog to digital converter 42 to produce digital signals X_1, X_2 and X_3 for use by the sensor processing subsystem 25. The sensor processing subsystem 25 shown in greater detail in figure 2 embodies both neural network 48 and fuzzy logic 46 processing of the inputs X_1, X_2 and X_3. Thus the neural/fuzzy processing subsystem 25 utilizes the amplitudes of UV, visible and IR radiation emanating from the weld zone 32, observed from a single point, as system inputs. Incoming data are analyzed independently by both the fuzzy logic system 46 and the neural

network 48. The result of the analysis performed by the fuzzy logic section is fed into an output node 60 of the neural network as an ancillary input. The implementation of the fuzzy logic system and a neural network is described in greater detail below.

Before describing the implementation of the neural network and fuzzy logic system we first present a background to neural networks. The dominant criterion in the design of the neural network 48 has been the processing time since this network is intended as a real-time process controller. The neural network portion of the system is designed as a self-inhibiting shallow network to increase the process speed. The network does not require off-line training since the attributes of inter cell connections is varied during the process. This particular characteristic makes this system completely insensitive to material and joint variations.

In its most general definition, a neural network is a collection of interconnected, calculating units (Neuron) that are organized in such a way that given a set of inputs to such a system, the output is the "expected" response. Each neuron produces an output based on its inputs and a pre-determined response function. Generally the term "pre-determined response function" consists of combination of adjustable scalars and transfer functions. The purpose of the teaching phase of a network is to determine the appropriate values for all adjustable scalars within the overall network so that the desired response from the network can be obtained for a given set of inputs. This implies that the values of the adjustable constants remain static after the teaching phase of the network.

The key to a neural network design and teaching is the knowledge of the desired response from the network. Given this knowledge, training data sets can be generated and subsequently by using one of a myriad of teaching algorithms, the appropriate set of network constants can be generated.

In the subject application, the aim of the network is to identify the "unusual" or "out of the ordinary" instances within an incoming data stream. This necessitates either a complete definition of an "ordinary" data stream or in corollary, the definition of an extraordinary event. Given the fact that it is impossible to define either the "ordinary" or the "extraordinary" events in their entirety, the traditional approach to neural networks was abandoned.

Since it is impossible to generate all-inclusive training data sets for applications such as control of laser processing, it is in turn impossible to use static inter-neuronal connection weights within the neural network. Given this framework, the neurons of the subject network

generate outputs without the use of pre-determined weights. Instead, the temporal behavior of the network is the function of the incoming data stream and hence the term "Self Adapting".

Referring now to figure 2, a schematic diagram of the sensor processing system 25 embodying the fuzzy logic system 46 and the neural network 48 is shown. Considering firstly the neural network 48, in a general embodiment the neural-network 48 comprises an input buffer layer 55 for preprocessing each of the input data channels Xi; groups of first layer neurons 54 for receiving the preprocessed data; second layer neurons 58 connected to receive outputs from the first layer neurons and an output node neuron 60, which receives data from all the second layer neurons.

The outputs from the input layer neurons are passed on to the second layer neurons 58 when the values of the neurons are above a predetermined threshold. The second layer neurons allow the output from the first layer neurons to pass to the third layer 60 neuron if its input exceeds a predetermined threshold value, if none of the outputs from the first layer neurons exceeds the threshold value then the highest non-zero value is taken as an output and passed on to the third layer neuron. Thus it may be seen that the second layer neurons 54 provide a value indicative of the significance of its respective input channel. In this embodiment these will be values indicating the relative strength of the IR, UV or VI channels above a generally ambient or non-significant value.

The last node 60 of the network gathers information not only from three upstream channels of the neural network but also from the fuzzy logic section 46 (described in detail below). Based on these inputs to the last node 60 a decision is made on whether to change the weld parameters or not. This portion of the control routine is highly dependent on the specifics of the part being welded and therefore always custom designed for a specific application. The last node processes a series of "if-then" statements or conditional statements, the result of which is the appropriate action for the controller to take e.g. to slow down the weld by 10%.

As can be deduced from the above description of the neural network, the neural network section 48 does not analyze the data directly but it analyses the input frequency to various sub channels. Small FIFO buffers 56 are utilized for each channel as part of the input-layer cell processing. These buffers construct histograms of incoming data on a continuous basis. Time derivatives of the standard deviations and the averages of the contents of these

buffers are then used as triggers to indicate extraordinary events. Unless these triggers occur, the input layer neurons inhibit themselves and no further processing occurs for that particular set of data. This self-inhibiting characteristic improves the overall information processing time for the system. The network responds to variations in the incoming data stream. In another words, it is highly specialized in identifying the "unusual" events. Given this characteristic, if the incoming data originates from a gradually degrading weld then the neural network will be insensitive to it and therefore will not be able to identify the weld as a "bad" weld. Hence the necessity for an independent fuzzy node.

Referring again to figure 2, the preprocessing in the buffers is achieved by first computing histograms of incoming data. For the histogram construction, let $u(t)$ be the amplitude of one of the channel signals Xi at time t, which is bounded from below and above i.e. $0 \le u(t) \le U$ where U is a positive constant. For each of the channels Xi its input signal $u(t)$ is sampled with a sampling period of Δt yielding the sequence u_i with

$$u_i = u(i\,\Delta t) \quad \text{where } i = 0,1,2....$$

Blocks of N u_i's are then used to construct a histogram with B bins. Typically there are 8 to 16 bins, but it may vary depending on the specfic application. Let h_{jm} be the value of the j^{th} bin in the histogram for the m^{th} block. This value is determined by

$$h_{jm} = \sum_{i=mN}^{(m+1)N-1} f\left(u_i,\ j\frac{U}{B},\ (j+1)\frac{U}{B}\right),$$
$$\text{where } f(a,b,c) = \begin{cases} 1 & \text{if } b \le a < c \\ 0 & \text{otherwise} \end{cases}$$
$$\text{and } j = 0, 1, 2, ..., B-1 \quad ; \quad m = 0, 1, 2, ...$$

Next running averages a_{jk} and standard deviation σ_{jk} values of histogram the bins are calculated using a moving window of length A; i.e.

$$a_{jk} = \frac{1}{A} \sum_{m=k-A+1}^{k} h_{jm}$$
$$\text{where } k = A, A+1, A+2, \ldots$$

Similarly the running standard deviation for the jth bin at time k is given by

$$\sigma_{jk} = \sqrt{\frac{1}{A-1} \sum_{m=k-A+1}^{k} \left(h_{jm} - a_{jk}\right)^2}$$

where $k = A, A+1, A+2, ..$

The differentials of averages and standard deviations are calculated as follows:

$$\Delta a_{jk} = a_{jk} - a_{j(k-1)}$$
$$\Delta \sigma_{jk} = \sigma_{jk} - \sigma_{j(k-1)}$$

The percent changes in differentials are given by:

$$\%a_{jk} = \frac{\Delta a_{jk} - \Delta a_{j(k-1)}}{\Delta a_{j(k-1)}}$$
$$\%\sigma_{jk} = \frac{\Delta \sigma_{jk} - \Delta \sigma_{(k-1)}}{\Delta \sigma_{j(k-1)}}$$

An unusual change in a and σ, as detected by the rule:

$$\%a_{jk} > T_a \quad \text{and} \quad \%\sigma_{\mathrm{jk}} > T_\sigma$$

for any j, where T_a and T_σ are the threshold constants, triggers the following computations in the first layer neurons of the first differential of average values as follows:

$$\Delta_1 a_{jk} = \frac{a_{j(k+\zeta)} - a_{jk}}{\zeta}$$

$$\Delta_2 a_{jk} = \frac{a_{j(k+\zeta)} - a_{j\delta}}{\zeta}$$

Where $\zeta = \delta = \frac{T}{2}$ if T is even, $\zeta = \frac{T-1}{2}$ and $\delta = \frac{T+1}{2}$ if T is odd

Let T the time interval to compute two snapshots of first derivatives $\Delta_1 a_{jk}$ and $\Delta_2 a_{jk}$ of averages. Then using these values the significance, S, of any weld fault is assessed as follows. If for any j

$$\left|\Delta_1 a_{jk}\right| \geq K \quad \text{or} \quad \left|\Delta_2 a_{jk}\right| \geq K \quad \text{where K is a constant}$$

then $S = 3$. Otherwise if

$$K' \leq \left|\Delta_1 a_{jk}\right| < K \quad \text{and} \quad K' \leq \left|\Delta_2 a_{jk}\right| < K$$

Then S = 2, else S = 1. Thus, the higher the value of S value then the higher the significance of the detected event.

Next a second differential of average and standard deviation values is computed. If a "trigger" occurs at time k, as described above, the number of negative slopes between consecutive events $\Delta\sigma_{jk}$, as denoted by C $\bar{o}j$ is computed as follows

$$C_{\sigma j} = \sum_{i=k}^{k+D} \mathrm{stp}\left(\Delta\sigma_{ji} - \Delta\sigma_{j(i+1)}\right)$$

where $\mathrm{stp}(a) = \begin{cases} 1 & \text{if} \quad a > 0 \\ 0 & \text{otherwise} \end{cases}$, k = 2,3,... and D is a positive constant

Similar formulae apply to the average values.

The Spread and magnitude of the data distribution Ψ is calculated as follows. The first differential of the network input is calculated as:

$$\Delta h_{jm} = h_{jm} - h_{j(m-1)}$$

if Δhjm = 0 for all j, then let sp=0 and mg=0. The variables Sp and mg are associated with the spread, $sp = |j - \eta|$, of the data between channels histogram structure and the magnitude of this spread, respectively.

Otherwise let j be the largest index of the cell with the maximum Δh value, $\max_j \{\Delta h_{jk}\}$.

If there exist more than one maximum, than j is the largest index of the maxima. Similarly let η be the smallest index of the minimum, $\min_\eta \{\Delta h_{\eta k}\}$.

The magnitude mg is given by the following formula

$$mg = \max_j \{\Delta h_{jk}\}$$

The significance value Ψ is assigned using the sum sp + mg and normalizing it to a pre chosen constant.

The output of the first layer cells with index j of the neural network is determined as

$$\gamma_\varphi = 10 \times \frac{S_j + C_{\alpha j} + C_{aj}}{M_S + M_C} + \Psi$$

follows:

Where M_x are the maximum values of the variable x. The second layer cells receive as inputs the value γ from the first layer neurons in its channel. The output of the second layer cells, y_k is computed by, $y_k = g\left(\max_j \gamma_j\right)$ where the function g is a "linear-with hard-saturation" function i.e.

$$g(a) = \begin{cases} za_1 & \text{for } a \geq a_1 \\ za & \text{for } a_0 < a < a_1 \\ za_0 & \text{for } a \leq a_0 \end{cases}$$

with z being a positive constant and a_0, a_1 are the saturation constants. Furthermore the max γ value is computed by evaluating the γ across all channels, whereas the first layer neuron outputs evaluate only their respective channel input.

Referring now to the fuzzy logic portion , it analyses the data with respect to the signal amplitudes and orients the overall weld process within the universe of discourse outlined by the input and output membership functions of the fuzzy inference engine.

Fuzzy logic systems may be understood as numerical model-free estimators which map system state linguistic inputs such as a amplitude of UV light to a control output such as large positive change in weld speed in relation to laser welding with a visual encoder. Implementing the FLC requires the development of a set of rules that have the form of 'if-then' statements. The 'if' side of the rule that contain the antecedents correspond to the degree of membership calculated from the system input value, such as amplitude. The 'then' side of the rule or the consequent corresponds to the control output function. Thus, fuzzy

logic control procedures work well when appropriate fuzzy 'if-then' rules are provided, such as "if UV==SM and IR==SM then speed=VS".

For the fuzzy inference engine Sugeno style inference was chosen over Mamdani style due to process speed advantages of this system. Both styles are well known in the art and will not be described further. In the Sugeno system all output membership functions are singleton spikes. The fuzzy node inference engine consists of three inputs and a single output. The input membership functions are shown in figure 3 for UV, Visible and Infra Red input signal amplitudes whereas the output is weld quality.

The output membership function consists of three singleton values associated with welding speed. In this instance they are "OK" for do nothing, "SL" for slow down and "VS" for very slow. There are 20 rules associated with this application and they are highly process specific, and are shown in tabular form in figure 4, for IR versus UV, IR versus VI and UV versus VIS.

As briefly described earlier, the final node 60 of the network combines the information originating from the fuzzy logic 46 and the neural network 48 sides of the controller. A decision is then made by the controller whether to alter one of the welding process parameters or not based on independent analyses of the same set of input data to both the neural and the fuzzy sides of the overall controller. Once a decision is made it is executed in real time.

It may be seen that the inputs to the FLC are the raw data derived from the IR, UV and VI channels. This is to be contrasted with the inputs to the neural-network which are the frequency of occurrence of the input data values within specific ranges. The FLC processes these inputs and produces an output which is written into a separate buffer at the output node 60 as shown in figure 6(c). This buffer is also processed in a similar manner to the neural-network buffers, resulting in a single number constituting the FLC output. Finally the neural-network output and the FLC output is averaged to create a weld quality number for that instant.

It is to be further noted that in this specific application welding speed is only reduced (never increased) due to the very short weld duration (approximately three seconds). The speed correction portion of the last neural node processes only the last entry to both the neural-network and the FLC buffers. If either of these entries are greater than a preset

threshold the controller slows the welding speed by a preset threshold. If the weld duration is long however then it is possible to derive an algorithm to change the speed both in a positive or negative direction. It may be seen that three singletons are output namely VS = 0, MS = 6 and OK = 10.

A more graphical representation of the neural network is shown in Figures 6(a), 6(b) and 6(c). In this example assume each of the input channels is sorted according to a selection rule. In the present embodiment the selection rule represents successive range divisions across the entire channel amplitude range. In other words the input signal amplitude is classified at any given point in time as falling within one of for example eight successive input ranges, for example of the input signal values from 0 to 800. Then the ranges may be divided as 0 - 200, 201 - 300 ... 701 - 800. A selector 74 produces one of eight output signals dependent on whether the input signal amplitude from its respective channel falls within the corresponding range. Each of these outputs shall be referred to as $\alpha_1, \alpha_2, \alpha_3 \ldots \alpha_8$. As noted earlier these rules may be changed in accordance with the application and is merely exemplary for the embodiment described.

The outputs from the respective selector 62 for each of the channels is then fed to a respective neuron of the first neural layer. For example, assume there are eight first layer neurons for the first channel, these neurons $N_{11}, N_{12}, N_{13} \ldots N_{18}$ receive as inputs the signals $\alpha_1, \alpha_2, \ldots \alpha_8$ from the first channel selector, similarly for the second and third channels respectively.

Each of the neurons in the first channel perform functions which modify the relative weights of the data.

Referring to figure 6(a), a detailed representation of the layer one activity is shown. In this implementation, the respective channels, IR, VI and UV analog signals are fed into an analog to digital converter the inputs of which are stored in respective registers 72. For convenience only one of these channels is shown. It is assumed that the outputs of the analog digital converters are sampled every t seconds. The input buffer 72 is then read and applied to the selector 74 to determine which of the ranges the input falls within, that is associated with each of the selection ranges in a cell 76. In other words the value of each of the cells is incremented by one if the contents of the input register falls within the selected range

corresponding to that cell. After a predetermined number of samples, for example ten samples, each of the cells is scanned and the contents of the cell is output to its respective FIFO buffer 78. Next at a predetermined time the average value of the elements in a FIFO buffer 78 are calculated and stored in a second FIFO buffer 80. Also the standard deviation of the FIFO buffer 78 is calculated and stored in its respective FIFO buffer 82. Next the difference between the first and second value in the average FIFO buffer 80 is calculated and stored in a third buffer 84. Similarly the difference between the first and second value in the standard deviation FIFO buffer is calculated and stored in a fourth buffer 86. Next the past Δ average and the past Δ standard deviation are calculated and stored in respective buffers 88 and 90.

Each of the cells are then given three significance numbers. The first significance number is indicative of the percentage difference of the average and the percentage difference of the standard deviation being above predetermined threshold values. The second significance number looks at the slopes or the past averages buffer and the past standard deviations buffer and the third significance number is produced by observing any sign of changes in the Δ average and the Δ standard deviation buffers. These three significance numbers are then combined to generate a single significance number for that cell. This final significance number acts as a feedback weight when the cell is modified. Cell modification occurs by looking at the spread in data between all cells. The cell is modified by a value determined from the significance number for that cell which indicates how wide the spread is between data for the cells. Thus in this final step the spread looks at all cells and generally picks the top two cells where the spread is the greatest. Thus when any of the cells are above a predetermined value the cell value is the neuron value which is then output to the next layer neuron.

As seen in figure 6(b), in layer two each of the neurons comprises an input buffer 96 of length equivalent to the number of cells in the previous layer. For example, neuron 1 of layer two will comprise an eight element buffer. In layer two each of the elements of the buffer is scanned and checked against the threshold value. If the element in the buffer is greater than the threshold this is then output to the layer three neuron or if the value is less than the threshold then the first non-zero value is used as an output to the layer three neuron.

The last neural-network node as shown in figure 6(c) accepts inputs from the UV, IR

and VI channels as well as the FLC engine. This last node produces two outputs: 1) a weld quality number and 2) a speed correction. This last node incorporates a large buffer in which all the individual channels significance numbers are entered. At any given time this node processes all the inputs to the buffer by first separating all its inputs to be either higher or lower than a given threshold. Entries that are higher than the threshold are weighted and then all the weighted entries are averaged. This averaged single number constitutes the output of the neural-network. It is to be noted that the last node incorporates three neural-network buffers and one FLC buffer.

Although the invention has been described with reference to certain specific embodiments, various modifications thereof will be apparent to those skilled in the art without departing from the spirit and scope of the invention as outlined in the claims appended hereto. For example the present neural network may bee used in other applications where extraordinary events are to be detected in an incoming data stream eg. detecting a signal in noise.

THE EMBODIMENTS OF THE INVENTION IN WHICH AN EXCLUSIVE PROPERTY OR PRIVILEGE IS CLAIMED ARE DEFINED AS FOLLOWS:

1. A control system for laser processing of a material, the system comprising:

a sensor for receiving electro-magnetic emissions from a weld zone and producing data signals indicative thereof;

a fuzzy logic subsystem for processing said sensor outputs directly to produce a weld quality output signal;

neural network subsystem using input data frequency from said sensor outputs and said weld quality signal to develop a weld parameter control signal; and

a controller for receiving said weld parameter control signal and adjusting said laser processing in response to variations thereof; whereby the neural network is cable of detecting extraordinary events in the incoming data stream while the fuzzy logic controller is capable of detecting trends in the incoming data stream; and

2. A neural network for detecting extraordinary events within an incoming data stream, said network comprising:

a plurality of input channels for receiving input data streams;

input buffers for preprocessing said input data to produce input data frequencies;

groups of first layer neurons associated with each channel for receiving said preprocessed data from said buffers;

second layer neurons connected to said first layer neurons to receive outputs from said first layer neurons; and

an output neuron for processing said outputs of all said second layer according to predetermined conditional statements for producing an output for indicating the relative significance of one of said channels.

3. A neural network as defined in Claim 2, said input buffers constructing histograms of said incoming data.

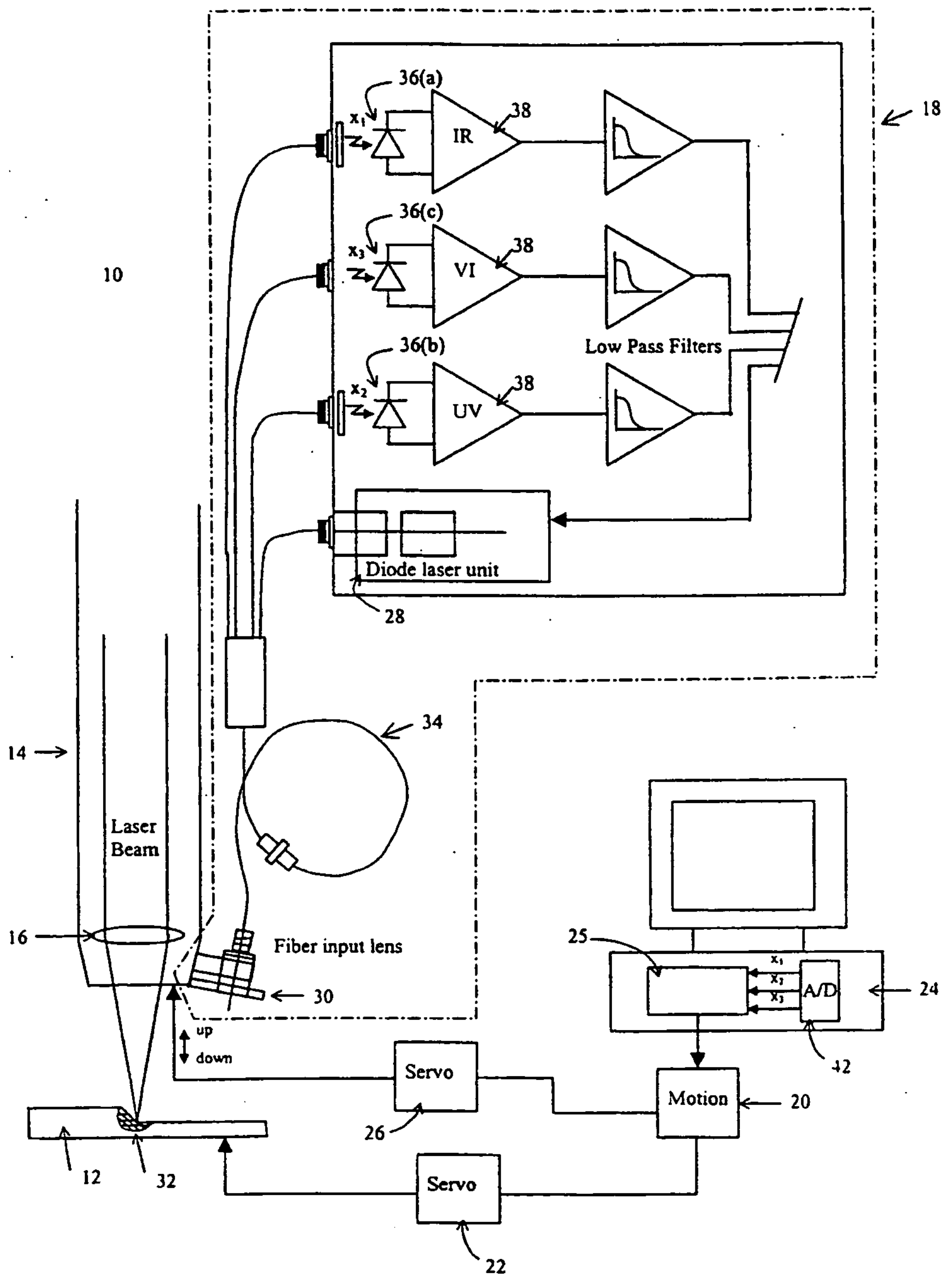
36(a)
38
IR
x_1
18
36(c)
38
VI
x_3
10
36(b)
Low Pass Filters
38
UV
x_2
Diode laser unit
28
34
14
Laser
Beam
16
Fiber input lens
30
25
x_1
x_2
x_3
A/D
24
42
up
down
Servo
Motion
20
26
12
32
Servo
22

Figure 1.

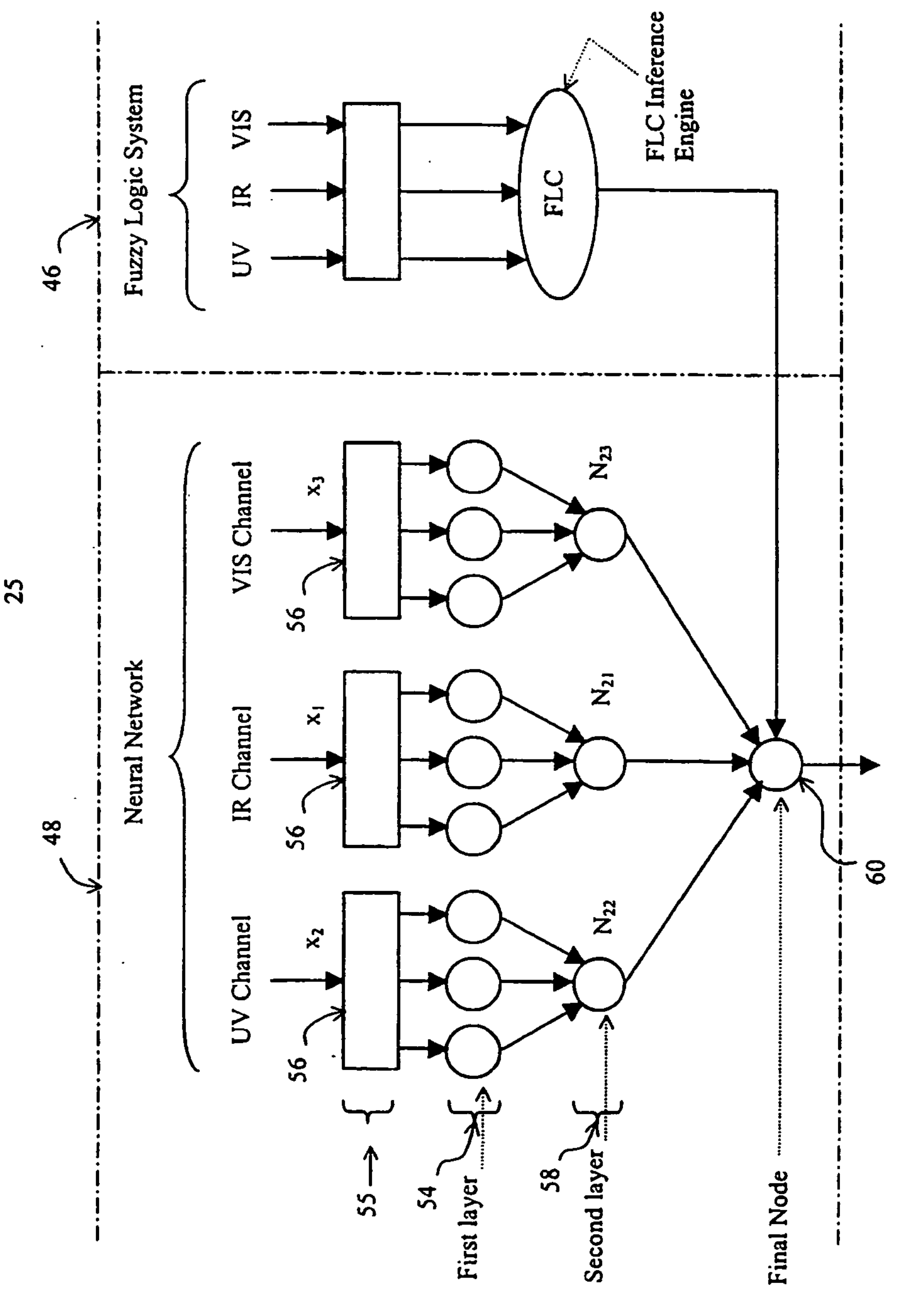
25
46
Fuzzy Logic System
UV
IR
VIS
FLC
FLC Inference Engine
48
Neural Network
UV Channel
IR Channel
VIS Channel
x_2
x_1
x_3
56
56
56
N_{22}
N_{21}
N_{23}
55
54
First layer
58
Second layer
Final Node
60

Figure 2.

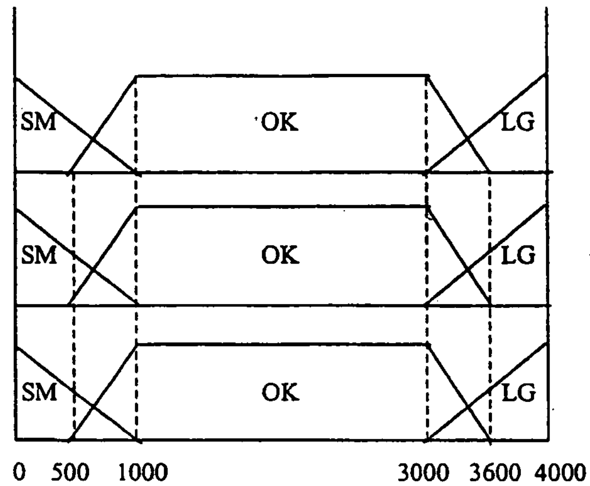

Figure 3.

UV \ IR	SM	OK	LG
SM	VS	MS	
OK	MS	OK	OK
LG		OK	VS

VIS \ IR	SM	OK	LG
SM	VS	MS	
OK	MS	OK	
LG			VS

UV \ VIS	SM	OK	LG
SM	VS	MS	
OK	MS	OK	OK
LG		OK	VS

Figure 4.

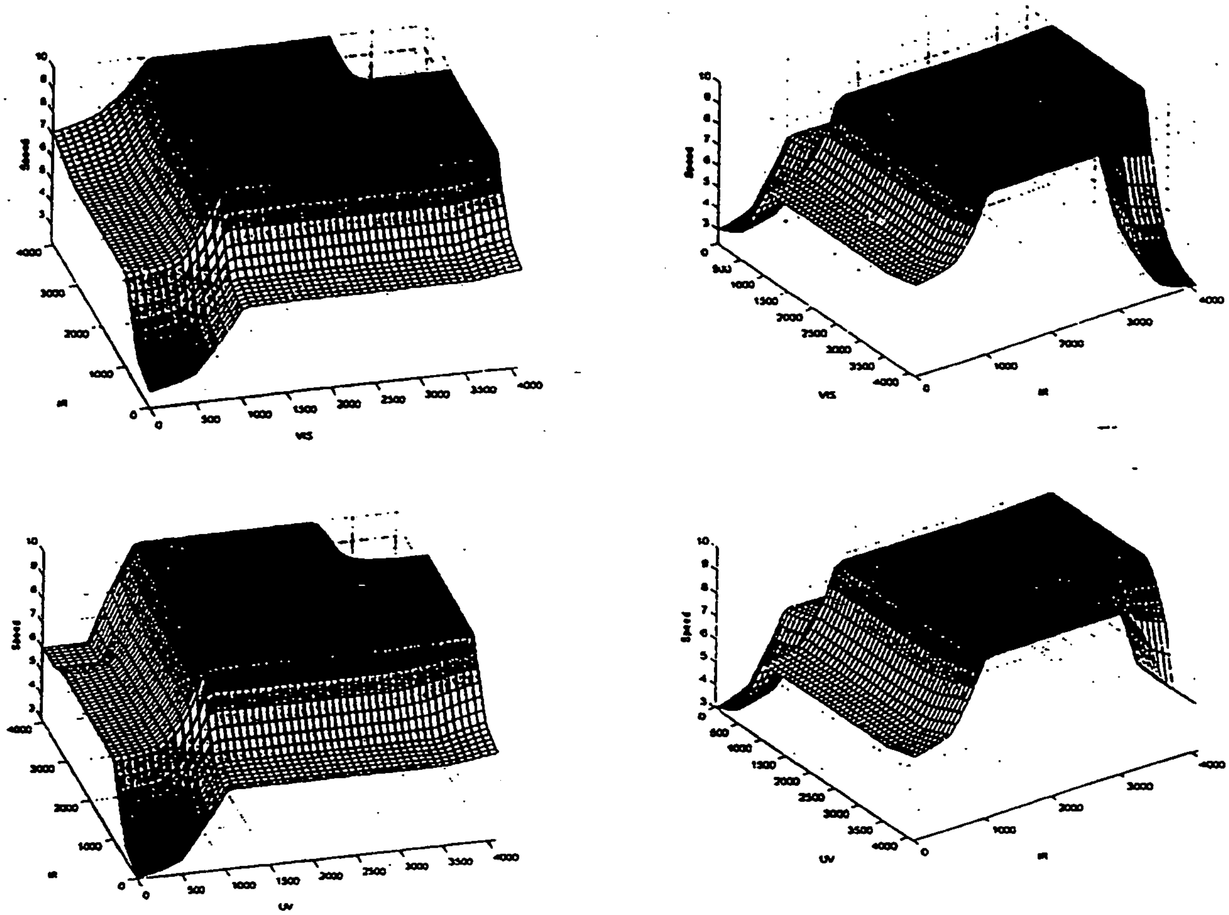

Figure 5 8

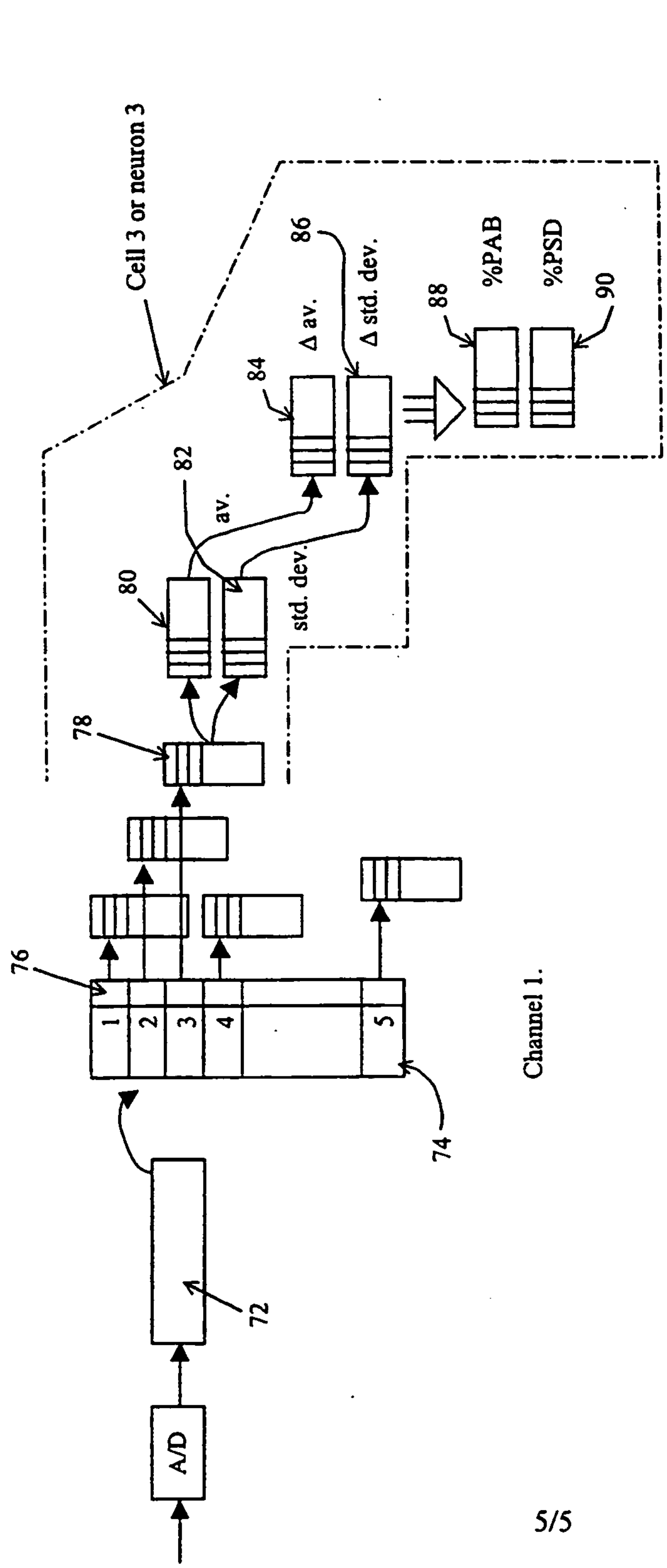

Figure 6(a).

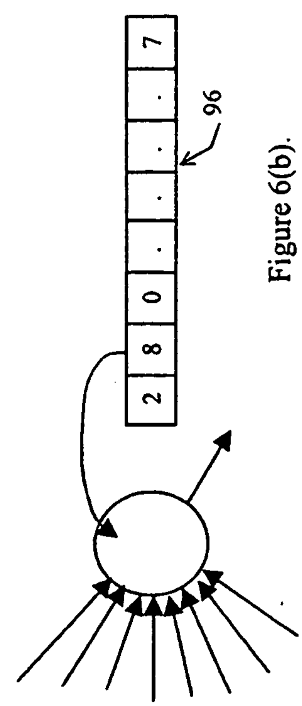

Figure 6(b).

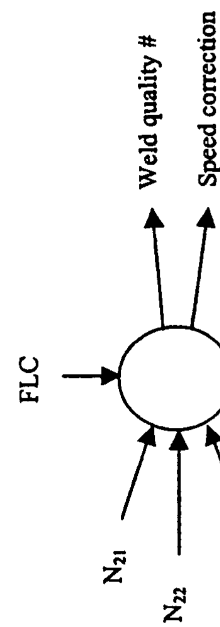

Figure 6(c).